LOW COST ROBUST BLUR ESTIMATOR

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ABSTRACT

A novel local blur estimation method is presented in the paper. Focal blur process is usually modeled as a Gaussian low-pass filtering and then the problem of blur estimation is to identify the Gaussian blur kernel. In the proposed method, the input blurred image first is re-blurred by Gaussian blur kernels with different blur radii. Then the difference ratios between the multiple re-blurred images and the input image are used to determine the unknown blur radius. We show that the proposed method does not require edge detection pre-processing and can estimate a wide range of blur. Experimental results of the proposed method on both synthetic and natural images compared with other methods are presented.

1. INTRODUCTION

Focal blur, or out-of-focus blur in images and videos occurs when objects in the scene are placed out of the focal range of the camera [1]. This is sometimes used by photographers to draw the viewers' attention to objects in focus, but in many cases it is desirable to remove the blur and restore the original scene faithfully. As objects at varying distances are differently blurred in the image, accurate blur estimation is essential. The estimation of focal blur has also become an important topic in many other applications, such as restoring the blurred background part of images and videos, digital auto-focusing system and 2D to 3D image conversion [3].

Focal blur is usually modeled as Gaussian blurring [2]. Therefore, the problem of blur estimation is to identify the Gaussian point spread function (PSF). Many techniques have been proposed to address the problem. Early blur estimation methods examine the regular pattern of zeros from the blurred image in the frequency domain. These methods can only identify a certain class of PSFs, but not truncated Gaussian PSFs which do not have zeros in the frequency domain. More recently parametric methods based on autoregressive moving-average (ARMA) models have been proposed [4] [5]. The blur estimation becomes the identification of the ARMA model and maximum likelihood (ML) estimation algorithm is employed for the estimation. However these methods are com-putationally intensive and lack a direct solution for the estimation. Recently, a blur estimation method from the work of Elder [6] receives considerable attention [7] [8]. In Elder's method, the blurred edge signal is convolved with a filter that is the second derivative of a Gaussian function and the response has a positive and a negative peak. The distance between these peak positions is used to determine the blur radius. A problem of Elder's method is that the blur estimation is easily deteriorated by the response of neighboring edges.

In this paper, we propose a new blur estimation method based on the difference between re-blurred versions of an image. Through an analysis performed on an edge model, we show that the blur radius can be easily calculated from the difference ratio, independent from the edge amplitude or position. The observation shows that the maximum of difference ratio appears at the edge position. This suggests that the proposed blur estimation does not require detection of edge position and angle. Furthermore, the proposed method demonstrates robust estimation even in areas with multiple neighboring edges. Experimental results on synthetic and natural images of the proposed method show favorable results.

The rest of the paper is organized as follows. In Section 2, we present the proposed blur estimation algorithm and its analysis based on an ideal edge model. Section 3 shows some experimental results on both synthetic and natural images, compared with Elder's method. Finally, we draw our conclusion in Section 4.

2. THE PROPOSED ALGORITHM

We introduce our proposed blur estimation algorithm based on an ideal edge and a blur kernel. The edge is modeled as a step function with amplitude A and offset B. For a discrete signal, the edge $f(x)$ shown in Fig. 1 is

$$f(x) = \begin{cases} A + B, & x \geq 0 \\ B, & x < 0 \end{cases} , x \in I \qquad (1)$$

where x is the position. The focal blur kernel is modeled by
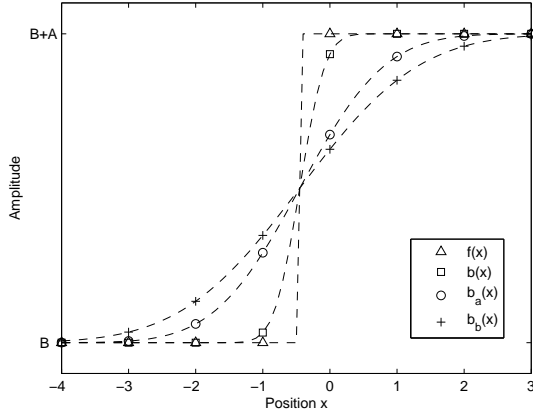
Fig. 1. The step edge $f(x)$, the blurred edge $b(x)$ and its two re-blurred versions $b_a(x)$, $b_b(x)$

Fig. 2. Difference ratio among the edge

the normalized Gaussian function:

$$g(n, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{n^2}{2\sigma^2}\right), n \in I \quad (2)$$

where σ is the unknown blur radius to be estimated. For the normalized Gaussian function, we have:

$$\sum_{n \in I} g(n, \sigma) = \sum_{n \in I} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{n^2}{2\sigma^2}\right) = 1 \quad (3)$$
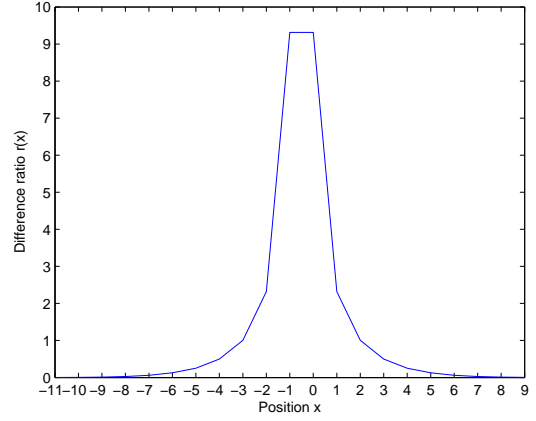
Then the blurred edge $b(x)$ will be:

$$b(x) = \sum_{n \in I} f(x - n)g(n, \sigma)$$

$$= \begin{cases} \frac{A}{2}\left(1 + \sum_{n=-x}^{x} g(n, \sigma)\right) + B, & x \geq 0 \\ \frac{A}{2}\left(1 - \sum_{n=x+1}^{-x-1} g(n, \sigma)\right) + B, & x < 0 \end{cases}, x \in I \quad (4)$$

As the convolution of two Gaussian functions with blur radiuses σ_1, σ_2 is:

$$g(n, \sigma_1) * g(n, \sigma_2) = g(n, \sqrt{\sigma_1^2 + \sigma_2^2}) \quad (5)$$

re-blurring the blurred edge using Gaussian blur kernels with blur radius σ_a and σ_b ($\sigma_b > \sigma_a$), results in two re-blurred versions $b_a(x)$ and $b_b(x)$:

$$b_a(x) = \begin{cases} \frac{A}{2}\left(1 + \sum_{n=-x}^{x} g(n, \sqrt{\sigma^2 + \sigma_a^2})\right) + B, & x \geq 0 \\ \frac{A}{2}\left(1 - \sum_{n=x+1}^{-x-1} g(n, \sqrt{\sigma^2 + \sigma_a^2})\right) + B, & x < 0 \end{cases},$$

$$b_b(x) = \begin{cases} \frac{A}{2}\left(1 + \sum_{n=-x}^{x} g(n, \sqrt{\sigma^2 + \sigma_b^2})\right) + B, & x \geq 0 \\ \frac{A}{2}\left(1 - \sum_{n=x+1}^{-x-1} g(n, \sqrt{\sigma^2 + \sigma_b^2})\right) + B, & x < 0 \end{cases},$$

$$x \in I \quad (6)$$

To make the blur estimation independent of the amplitude and offset of edges, we calculate the ratio $r(x)$ of the differences between the original blurred edge and the two re-blurred versions for every position x:

$$r(x) = \frac{b(x) - b_a(x)}{b_a(x) - b_b(x)} =$$

$$\begin{cases} \dfrac{\sum_{n=-x}^{x}\left(g(n, \sqrt{\sigma^2 + \sigma_a^2}) - g(n, \sigma)\right)}{\sum_{n=-x}^{x}\left(g(n, \sqrt{\sigma^2 + \sigma_b^2}) - g(n, \sqrt{\sigma^2 + \sigma_a^2})\right)}, & x \geq 0 \\[2em] \dfrac{\sum_{n=x+1}^{-x-1}\left(g(n, \sqrt{\sigma^2 + \sigma_a^2}) - g(n, \sigma)\right)}{\sum_{n=x+1}^{-x-1}\left(g(n, \sqrt{\sigma^2 + \sigma_b^2}) - g(n, \sqrt{\sigma^2 + \sigma_a^2})\right)}, & x < 0 \end{cases} \quad (7)$$

The difference ratio peaks at the edge position $x = -1, 0$ as shown in Fig. 2. So we obtain:

$$r(x)_{max} = r(-1) = r(0) = \frac{\frac{1}{\sigma} - \frac{1}{\sqrt{\sigma^2 + \sigma_a^2}}}{\frac{1}{\sqrt{\sigma^2 + \sigma_a^2}} - \frac{1}{\sqrt{\sigma^2 + \sigma_b^2}}} \quad (8)$$

When $\sigma_a, \sigma_b \gg \sigma$, we can use some approximations:

$$\sqrt{\sigma^2 + \sigma_a^2} \approx \sigma_a$$

$$\sqrt{\sigma^2 + \sigma_b^2} \approx \sigma_b$$

which we use to simplify Equation 8:

$$r(x)_{max} \approx \frac{\frac{1}{\sigma} - \frac{1}{\sigma_a}}{\frac{1}{\sigma_a} - \frac{1}{\sigma_b}} = \frac{(\frac{\sigma_a}{\sigma} - 1) \cdot \sigma_b}{\sigma_b - \sigma_a} \quad (9)$$

or

$$\sigma \approx \frac{\sigma_a \cdot \sigma_b}{(\sigma_b - \sigma_a) \cdot R + \sigma_b} \quad (10)$$

Equation 10 shows that blur radius σ can be calculated from the difference ratio maximum $r(x)_{max}$ and re-blur radius σ_a, σ_b, independent of the edge amplitude A and offset B. The identification of the local maximum of difference ratio $r(x)_{max}$ can not only estimate the blur radius but also locate the edge position, which implies the blur estimation requires any edge detection pre-processing. This helps to keep the complexity For the blur estimation in 2D images, we use 2D Gaussian blur kernel for the re-blurring. As any direction of a 2D Gaussian function is a 1D Gaussian function, the proposed blur estimation is also applicable. Using 2D Gaussian kernels for the estimation avoids detecting the angle of the edge or gradient, which is required in Elder's method.

3. EXPERIMENTS AND RESULTS

In this section, we test the proposed method on some synthetic and natural images, comparing with Elder's methods. For the synthetic images, we use multiple step edges blurred by a 1D Gaussian blur kernel, with the blur radius increasing linearly along the edge from 0.1 to 5, as shown in Fig. 3. About one percent Gaussian noise is added to simulate sensor noise. Different distances between neighboring step edges D has been used. We use the optimal settings for both meth-
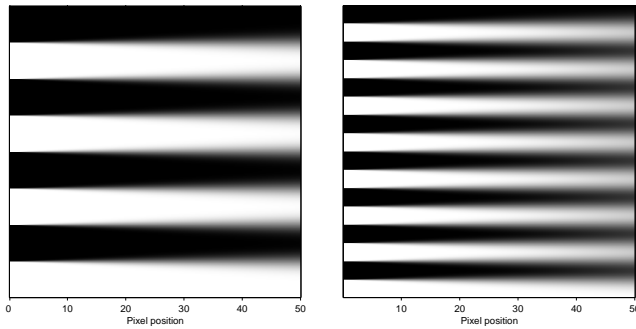

Fig. 3. Synthetic images

ods and the results are shown in Fig. 4, Fig. 5 and Fig. 6. As one can see, the distance between neighboring edges is relative large, which can be regarded as a single edge. Both methods can reliably estimate a wide range of blur. When the distance between neighboring edges becomes relative small,

Elder's method suffers considerably from the interference of neighboring edges and the estimation is very unreliable while the propose method demonstrates robust estimate.
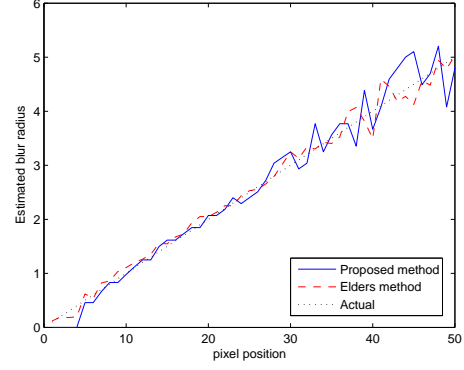
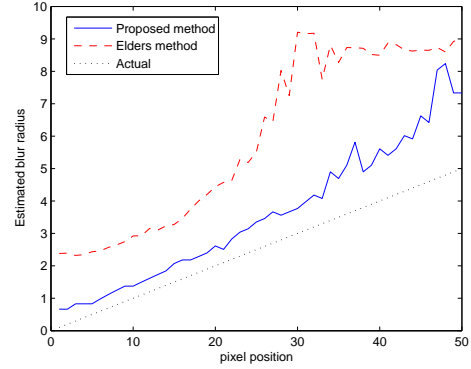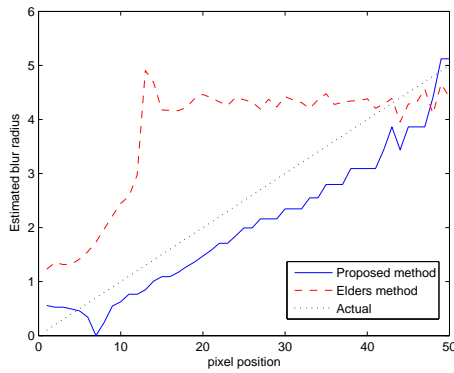

Fig. 4. Result with $D = 50$ pixels

Fig. 5. Result with $D = 20$ pixels

For natural images, we use Lena for the test. Blur estimation results of Elder's method and the proposed method have been illustrated in grey images.(Fig. 8 and Fig.9) Both methods are implemented in a block-based manner. 8×8 block has been used and we assume that the blur radius is the same within every block. In the blur estimation results, the lighter area indicate a larger blur radius, while the darker area indicate a smaller blur radius. We can see that the differently blurred background of Lena image has been estimated more accurately by the proposed method than Elder's method.

4. CONCLUSION

We have presented a novel robust, low-cost blur estimation algorithm. The maximum of difference ratio between an original image and its two re-blurred versions has been proposed

Fig. 6. Result with $D = 10$ pixels

Fig. 9. Results of the proposed method

to identify the edges and estimate the blur radius in the original image. The proposed method has been shown to have robust estimation, especially for the interference from neighboring edges. It also features easy implementation and merits further attention.

5. REFERENCES

[1] A. Pentland, "A New Sense for Depth of Field", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 9, No. 4, pp. 523-531, July 1987.

[2] A. Pentland, T. Darrell, M. Turk and W. Huang, "A Simple Real Time Range Camera", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 256-261, 1989.

[3] M. Goncalves and F. Ernst, "Single-image motion and camera blur identifocation", Technical report, Philips Research, Eindhoven, 2005. PR-TN-2005/00298.

[4] R. L. Lagendijk, A. M. Tekalp, and J. Biemond, "Maximum Likelihood Image and Blur Identification: A Unifying Approach", *Optical Engineering*, vol. 28 (5), pp. 422-435, 1990.

[5] G. Pavlovic, A. M. Tekalp,"Maximum likelihood parametric blur identification based on a continuous spatial domain model", *IEEE Transactions on Image Processing*, vol. 1, Issue 4, pp. 496-504, Oct. 1992.

[6] J. H. Elder and S. W. Zucker, "Local Scale Control for Edge Detection and Blur Estimation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 7, July 1998.

Fig. 7. Lena

Fig. 8. Result of Elder's method

[7] M. Basu, "Gaussian-based edge-detection methods-a survey", *IEEE Transactions on Systems, Man and Cybernetics, Part C*, Vol. 32, Issue 3, pp. 252-260, Aug. 2002.

[8] K. Suzuki, I. Horiba and N. Sugie, "Neural edge enhancer for supervised edge enhancement from noisy images", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 25, Issue 12, pp. 1582-1596, Dec. 2003.